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CLASSIFICATION OF SOILS THROUGH MACHINE LEARNING: A REVIEW AND EXPERIMENTAL IMPLEMENTATION

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ABSTRACT

This research presents a comprehensive review and experimental analysis on soil classification techniques utilizing both physicochemical properties and image-based data. A detailed examination of recent studies reveals that traditional Machine Learning (ML) models, such as Random Forest (RF) and Support Vector Machine (SVM), have achieved high accuracies (up to 96.48% and 98.4%) when classifying soils based on their physicochemical characteristics. With the increasing availability of soil image datasets, Deep Learning models, particularly nLmF-Convolutional Neural Networks (CNNs) and advanced variants like Convolutional Neural Networks (CNNs), have demonstrated competitive performance by effectively capturing spatial and textural features, achieving accuracies up to 96.25%. Furthermore, hybrid and ensemble models integrating CNNs with classifiers like SVM, k-NN, Naïve Bayes, and Decision Trees have contributed to improving the robustness of soil classification systems. Building upon these findings, an experimental CNN model was created and trained to categorize soil photos into five groups based on color and texture. The dataset, consisting 350 photos spanning five soil classes, was rigorously preprocessed, augmented and balanced before separating into training, test, and validation sets. Using the Adam optimizer with early stopping and learning rate reduction approaches, the CNN model—which was built with several convolutional layers, batch normalization, dropout layers, and softmax activation—was trained. The suggested model had a validation loss of 0.05 and a test accuracy of 98%. Detailed evaluation metrics, including classification reports, confusion matrices, and training-validation curves, confirmed the model's effectiveness. This work highlights the potential of CNN-based approaches for accurate soil classification and sets the groundwork for future research integrating soil classification with crop recommendation systems.

Keywords: Deep learning for soil texture and color, image-based soil prediction, machine learning in agriculture, classification of soil, convolutional neural networks (CNN), and precision agriculture.

1. INTRODUCTION

Soil classification is a foundational aspect of agricultural planning, geotechnical engineering, and environmental conservation. (Radhika, et al., 2019; Subramanyam et al., 2023). Accurate identification and categorization of soil types based on their physicochemical and textural properties is essential for selecting suitable crops, improving irrigation strategies, ensuring structural safety, and supporting sustainable land use (Ghanbarian et al., 2021; Waikar et al., 2020). Traditionally, methods like To evaluate soil properties, the Standard Penetration Test (SPT), Cone Penetration Test (CPT), and Pressuremeter Test (PMT) have been employed. (Wazoh et al., 2014)While these techniques are well-established in geotechnical applications and provide valuable empirical data, they are time-consuming, require specialized instruments and expertise, and are often site-specific (Cavallaro, 2020; Doe et al., 2023). These limitations pose significant challenges for large-scale or real-time agricultural use, especially in resource-constrained or remote areas (Srivastava et al., 2021; Saranya et al., 2024).

To overcome these challenges, machine learning (ML) has emerged as a transformative approach (Inazumi et al., 2020) . ML models are capable of processing large, heterogeneous datasets, learning from past examples, and making high-accuracy predictions without explicit programming (Waikar et al., 2020). Algorithms such as Decision Trees (DT), Support Vector Machines (SVM) (Vijay et al., 2020), Random Forests (RF), k-Nearest Neighbors (k-NN), and Deep Neural Networks (DNNs) have been extensively applied for soil classification using features like pH, salinity, nitrogen, phosphorus, potassium, moisture, and organic content (Rahman, 2024; Nguyen et al., 2022). These models can uncover complex, nonlinear relationships between soil parameters and soil types or fertility levels that are often difficult to model using traditional statistical techniques.

Additionally, soil classification has been transformed by the development of deep learning, particularly Convolutional Neural Networks (CNNs), which allow for the direct study of soil texture and color from image data. (Chetan et al., 2023) CNNs excel in feature extraction from high-dimensional image data, making them particularly suitable for soil texture-based classification, where visual patterns are critical (Patel et al., 2023; Gyasi et al., 2023). These models require minimal manual intervention and can be integrated into mobile or web-based platforms for real-time soil assessment, thus democratizing access to agricultural intelligence tools.

The significance of this study lies in its dual approach: reviewing both traditional and modern machine learning-based soil classification methods, and implementing a CNN-based image classification model for practical use (Manjari et al., 2023; Sonkamble et al., 2023). By leveraging a five-class soil image dataset, our work aims to automate the classification process, enhance prediction accuracy, and contribute to the development of intelligent crop recommendation systems. Such systems can optimize input usage, reduce costs, and increase yield — ultimately supporting food security and sustainable agriculture (Ahmed et al., 2024).

Furthermore, integrating image-based classification with ML-powered crop suggestion models can bridge the gap between soil diagnostics and precision farming. By providing farmers with practical insights, this all-encompassing strategy can help them make well-informed decisions about irrigation, fertilization, and crop rotation. The broader impact extends to environmental conservation, as data-driven land management can help in reducing soil degradation, improving water efficiency, and minimizing chemical usage.

In conclusion, while traditional soil classification techniques have laid the groundwork, machine learning offers scalable, adaptive, and efficient solutions for modern-day agricultural and environmental challenges. This work stands at the intersection of domain knowledge and artificial intelligence, paving the way for smarter, sustainable soil and crop management systems.

2. LITERATURE REVIEW

2.1 A Review of ML & DL Approaches for Soil Classification

In the realm of soil classification and crop recommendation, several machine learning models have emerged as top contenders due to their effectiveness in handling complex data patterns and ensuring precise predictions. The most notable models include:

Table 1: Comparative Evaluation of ML and DL Algorithms for Classifying Soils by Type

Author(s) and Year	Title of the Study	Dataset Used	Method Compared	Significant Outcomes
(Rahman, 2024)	“ Soil classification and crop cultivation prediction: A comparative study of machine learning models “	1542 soil samples that were taken from Bangladesh's Noakhali District's agricultural area make up the dataset. Qualities (Soil Characteristics): Organic matter, pH, salinity, sulfur, nitrogen, phosphorus-B, boron, Clay, clay loam, and loam are the different types of soil.	ML models: Naive Bayes (NB), Random Forest (RF), SVM, Decision Tree (DT), MLPNN, and Logistic Regression (LR).	This study used machine learning to enhance crop prediction and soil categorization, employing the Random Forest (RF) model to achieve 96.48% accuracy.
(Subramanyam et al., 2023)	“ Developing a soil classification and crop recommendation system using machine learning “	The soil image dataset in .zip format into the program and extract the soil images from the .zip file.	Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (K-NN)	SVM improved soil classification by analyzing soil features; Random Forest is preferred when the dataset size is large.

(Patel et al., 2023)	" Soil classification and crop prediction using convolutional neural network "	The soil image dataset has five classes, with more than 1000 photos in each training class and more than 500 images in each test class.	Convolutional Neural Network (CNN)	This research helped farmers predict crop yields and recommend suitable crops, achieving 95% accuracy using Convolutional Neural Network (CNN).
(Manjari et al., 2023).	"A deep learning model for soil detection and crop recommendation for small farmers "	The study utilized a soil dataset with various soil compositions for classification and crop recommendation.	Rule-based, statistical, traditional learning, CNN**;** future improvements with GAN, GCN**.**	Deep learning methods enhanced agricultural productivity for land allocation and farmer classification; CNN achieved 96.25% accuracy with a 0.1606 loss.
(Navghare et al., 2023)	"Soil Classification Using Machine Learning and Crop Suggestion "	The paper uses structured agricultural datasets, including soil and crop parameters, environmental factors, and historical data for training machine learning models	KNN, SVM, and Decision Tree.(KNN)	SVM and KNN were used for crop yield prediction; SVM generally performs better for classification tasks based on environmental parameters.
(Gyasi et al., 2023)	"Advancements in Soil Classification: An In-Depth Analysis of Current Deep Learning Techniques and Emerging Trends "	diverse datasets; LUCAS Soil is publicly available, but field-prepared datasets are crucial for real-time classification.	Convolutional Neural Networks (CNNs),Transfe r Learning Models, Multi-Task Learning Models, Lightweight Deep Learning Models	Soil classification is crucial for agriculture, environment, and civil engineering applications; CNN models performed best for this task.
(Chala, et al., 2023)	"Assessing the Performance of Machine Learning Algorithms for Soil Classification Using Cone Penetration Test Data "	Public CPT datasets were preprocessed using Excel, analyzed, cleaned, and split for ML classification without applying data balancing.	The study utilized ANN, RF, SVM, and DT with Bayesian optimization and cross-validation on CPT data for performance evaluation.	This research enabled low-cost, efficient soil classification using ML models, achieving a very high accuracy of 99.84% with SVM.
(Nguyen, et al., 2022)	" Novel approach for soil classification using machine learning methods "	samples of soil from projects in Vietnam. Input Parameters: The samples are categorized using 15 soil parameters as features. Five soil classifications are the output: clayey sand (SC), fat clay (CH), lean clay (CL), elastic silt (MH), and silt (ML).	SVC, Multilayer Perceptron (MLP), RF	Precision agriculture and soil health monitoring were enhanced using ML models; Support Vector Classification (SVC) achieved 98.4% accuracy.

Gaikwad, et al., 2022).	"Soil Classification and Crop Suggestion using Machine Learning Techniques "	Soil Dataset: Contains chemical features of soil with class labels for soil series classification. Number of Samples: 383 , Classes: 11 soil series classes. Source: Soil Resources Development Institute (SRDI) of Bangladesh.	Weighted K-NN, Gaussian Kernel-Based SVM, Bagged Tree	Machine learning and image processing classified soils and recommended crops effectively; Gaussian Kernel-Based SVM achieved 94.95% accuracy.
(Blesslin et al., 2022)	" Machine Learning Algorithm for Soil Analysis and Classification of Micronutrients in IoT-Enabled Automated Farms "	Region: Mulberry gardens in various districts of Tamil Nadu. (Salem, Tirupur, Coimbatore, and Erode.) 250 samples per district, totaling 1000 soil samples. The dataset captures soil properties, which can be grouped into chemical, physical, and fertility-related parameters: Boron (B), Organic Carbon (OC), and Potassium (K). The dataset comprises 4888 samples.	Extreme Learning Machine (ELM)	Tamil Nadu's soil fertility was analyzed using Extreme Learning Machine (ELM), optimizing classification for recommending better soil conditions.
(John, A., et al., 2022)	" Soil Classification and Crop Recommendation System "	Soil Data:-Soil types and their features. Soil properties (captured through images). Crop Data:- Types of crops suitable for different soil types. Crop-soil compatibility	An independent machine learning model, like k-NN or SVM	A machine learning-based system predicted soil quality via smartphones, enabling crop recommendations with 91% accuracy using Support Vector Machines (SVM).
(Motia et al., 2021)	" Ensemble classifier to support decisions on soil classification "	The ICRISAT (International Crops Research Institute for the Semi-Arid Tropics) repository. Soil Parameters: Chemical properties of the soil. Additional Information: Previous crop details, Location information, Farm owner details. This dataset contains field-level soil health data with spatial distribution from 13 districts in Andhra Pradesh (AP).	Decision Tree (DT), Naive Bayes (NB), K-Nearest Neighbor (k-NN), and Ensemble Classifier (EC) (a mix of k-NN, NB, and DT)	This research used CNN for soil classification, SVM for crop recommendation, and Ensemble Classifier models achieving 84% accuracy.
(Girme et al., 2021)	" Soil Classification Using Convolutional Neural Network And Crop Recommendation Based On Support Vector Machine "	Soil Dataset: Contains images of soil samples from the following classes: Red Soil, Black Soil, Clay Soil, Alluvial Soil	CNN, KNN	A web-based application for soil classification and crop recommendation was created utilizing enhanced nLmF-CNN and KNN models for farmers.

Based on the analysis of Table 1, it is observed that traditional ML models like RF and SVM have demonstrated high accuracy (up to 96.48% and 98.4%) for soil classification using physicochemical properties. With the availability of soil image datasets, deep learning models like CNNs and enhanced architectures such as nLmF-CNN have achieved notable performance (up to 96.25%) by effectively extracting spatial and textural features. Furthermore, hybrid models that integrate CNNs for feature extraction with classifiers like SVM and k-NN, as well as ensemble models combining k-NN, Naïve Bayes, and Decision Trees (achieving up to 84% accuracy), have improved the robustness of soil classification systems. These results demonstrate how combining several models can greatly improve soil classification precision and scalability in precision farming.

2.2 Future Research Directions in Soil Classification

Subramanyam et al., (2023) Future research should aim to improve soil classification by adopting advanced machine learning models, using larger and more diverse datasets, and integrating real-time environmental and climatic variables (Vijay et al., 2020). Hybrid architectures, such as CNNs combined with DNNs, can refine model accuracy, while addressing class imbalance and expanding regional applicability remains critical (Inazumi et al., 2020; Girme et al., 2021; Saranya et al., 2020). Advances in digital image processing, multispectral and hyperspectral imaging, and robust ensemble techniques can further enhance performance (Srivastava et al., 2021; Motia & Reddy, 2021). Incorporating IoT-based soil sensing and GPS mapping will enable real-time monitoring, high-resolution soil fertility mapping, and precise, site-specific crop recommendations (Chandan et al., 2018; Raut, et al., 2020). Future work should also explore multi-temporal data integration to improve the scalability and environmental adaptability of CNN-based soil classification systems (Li et al., 2021; Raghwarte et al., 2023).

3. MATERIAL AND MATHODS

3.1 Dataset Description

In this study, a curated soil image dataset comprising a total of 350 images representing five distinct soil types—Alluvial (88), Black (87), Clay (53), Red (66), and Yellow (56)—was utilized for developing a soil classification model. The images were sourced from an open-access repository on Kaggle, ensuring diversity and real-world relevance of the samples. Each soil class exhibits unique visual characteristics, particularly in terms of texture and color, which serve as the primary features for classification. The aim of this research is to leverage these visual parameters to construct a robust ML and DL models capable of accurately distinguishing between the five soil types. This approach supports efficient, image-based soil categorization, offering potential applications in precision agriculture and environmental monitoring.

3.2 Data Preprocessing

To prepare the soil image dataset for classification, a comprehensive pre-processing pipeline was implemented using Python, OpenCV, and Keras libraries. All images were first resized to a uniform 256×256 resolution and converted to JPEG format for consistency. Duplicates and incompatible files were removed during this step. By applying augmentation techniques including rotation, shifting, zooming, and horizontal flipping using Keras' ImageDataGenerator, the dataset was expanded from 350 to 3,000 photos, with 600 images per class, in order to solve class imbalance. Finally, all images were renamed sequentially (e.g., 1_alluvial.jpg, 2_black.jpg) to ensure organized, class-specific identification. This automated pipeline streamlined the preparation of a clean, balanced, and structured dataset for training the soil classification model.

3.3 Proposed Implementation Cnn-Based Soil Image Classification

Based on the insights from existing literature, our implementation focuses on soil classification using image data, utilizing deep learning strategies to get better results in image-based activities. A CNN model is adopted for this purpose due to its proven effectiveness in extracting detailed features from soil textures and color patterns. Five different soil classes' worth of photos are used to train the model, with augmented samples to address class imbalance. This approach is suitable for our use case as it minimizes manual feature engineering while maximizing classification accuracy. Techniques including data augmentation, dropout, and batch normalization are used to improve generalization and prevent overfitting. Based on current research findings, CNN stands out as the most appropriate and efficient model for soil classification using image data, offering both high accuracy and scalability for deployment in real-time agricultural systems.

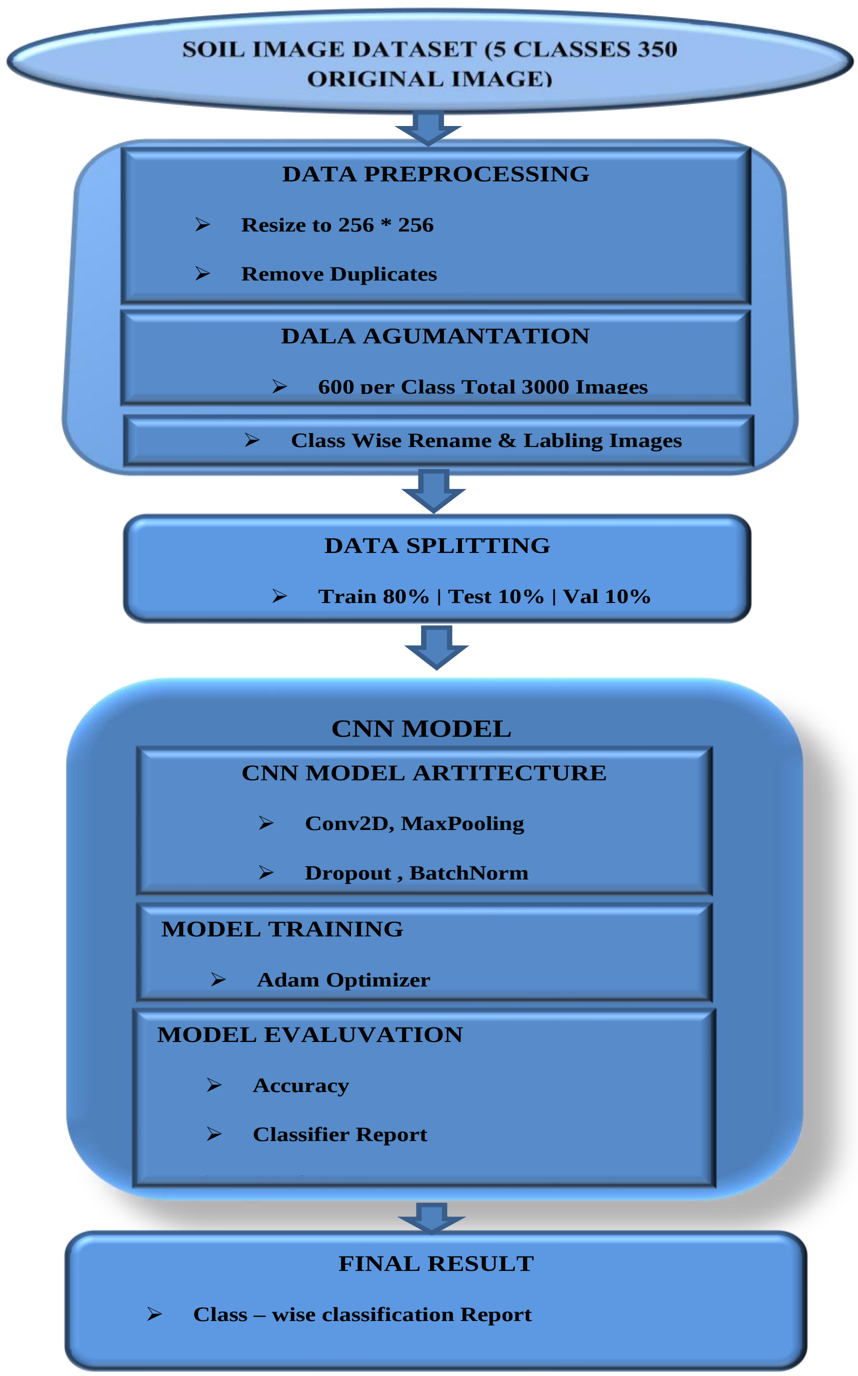

Figure 1: Proposed Workflow for Soil Image Classification using CNN

A CNN architecture was created and trained using the TensorFlow and Keras frameworks in order to categorize soil photographs according to their texture and color. The preprocessed dataset, consisting of uniformly resized images (256×256 pixels), was loaded using Keras' Image Data Generator with normalization (rescaling) and a 70-30 train-validation split. No additional augmentation was applied during training to preserve image integrity post-initial processing.

To stabilize training and minimize feature map size, the CNN model included many convolutional layers with increasing filters (32, 64, 128, 256), each followed by batch normalization and max pooling. To prevent overfitting, dropout was applied after the thick layer and deeper layers. Multi-class soil classification was done using a thick output layer activated by softmax. With a modest learning rate and categorical crossentropy loss, the Adam optimizer was used to assemble the model. To increase convergence and avoid overfitting, callbacks based on validation loss were employed for early halting and learning rate decrease.

Accuracy and a classification report with precision, recall, and F1-score were used to assess the model on the test data following up to 30 epochs of training. Plotting of accuracy and loss curves allowed for the visualization of training progress.

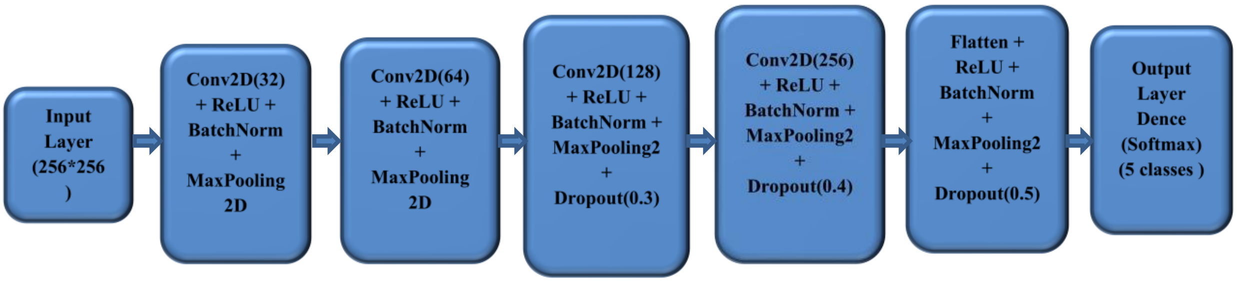

Figure 2 : CNN Architecture for Soil Classification

4. RESULT AND DISCUSSION

In this part, the experimental outcomes of the suggested Convolutional Neural Network (CNN) model for soil image classification are carefully examined. The model showed good classification performance when the dataset was carefully pre-processed, enhanced, and balanced across five different soil classifications. The model's efficacy was evaluated by computing key assessment metrics including accuracy, precision, recall, and F1-score. The results are compared with findings from previously reviewed studies, highlighting improvements achieved through customized CNN architecture and robust preprocessing techniques. Visualization tools, including confusion matrices and training-validation curves, further validate the model's stability, convergence, and generalization capabilities. A detailed class-wise performance discussion and insights into potential model enhancements are also presented.

Overall Model Performance: The model's validation loss was 0.05 and its overall accuracy was 98%. The training and validation curves indicate a smooth convergence without significant overfitting.

Classification Report Analysis: After analyzing the classification report, the performance of each soil class is quite promising, with some classes showing exceptional results. Both Red Soil and Clay Soil obtained perfect accuracy and memory scores; Red Soil had a perfect F1-score of 1.00 in addition to perfect precision and recall scores of 1.00. This suggests that the model correctly identified this class. With an accuracy of 0.95 and recall of 1.00, Black Soil and Alluvial Soil both showed excellent performance, suggesting that the model produced very few errors in these classifications. Yellow Soil's performance was nevertheless rather good with an accuracy of 1.00 and an F1-score of 0.98, despite its somewhat lower recall (0.97), which suggested some tiny misclassifications. Clay Soil displayed high precision (1.00) but slightly lower recall (0.93), which suggests that some misclassifications might have occurred, possibly due to visual similarities with other classes.
The micro average and weighted average both yielded precision, recall, and F1-scores of 0.98, confirming the model's strong generalization ability. These results indicate that the model has learned effectively and made balanced, reliable predictions across all classes. The model achieved an overall 98% accuracy, which is an excellent performance, especially considering the diversity of soil types.

Confusion Matrix Analysis: The confusion matrix (Figure 3) provides a detailed comparison between the true labels and predicted labels for each soil class, offering insights into model performance across various classes. True positives, or accurate classifications, are represented by diagonal elements, whereas misclassifications are represented by off-diagonal elements.

- **Red Soil:** Red Soil performed the best, with nearly all instances correctly classified, showing a high number of true positives and no significant misclassifications.
- **Yellow Soil and Alluvial Soil**: These two classes showed some overlap, with a few instances of Yellow Soil misclassified as Alluvial Soil and vice versa. This overlap may be due to similarities in color and texture features between these two soil types.
- **Clay Soil:** The model struggled slightly with distinguishing between Yellow Soil, Clay Soil, and Black Soil, with some misclassifications occurring between these classes. The visual similarity in texture and color among these soil types likely contributed to these errors.
- **Black Soil:** Although the model performed well overall, there were minor misclassifications of Black Soil instances as Yellow Soil and Clay Soil, but these were less frequent.

Overall, the confusion matrix shows that Red Soil was the most accurately classified class, while the Yellow Soil, Alluvial Soil, Clay Soil, and Black Soil classes exhibited some overlap. These misclassifications can be attributed to visual similarities in color and texture among certain soil types. The matrix highlights areas where the model can improve, particularly in distinguishing between similar-looking soil types, and suggests that further refinement in feature extraction or additional data augmentation may help address these challenges.

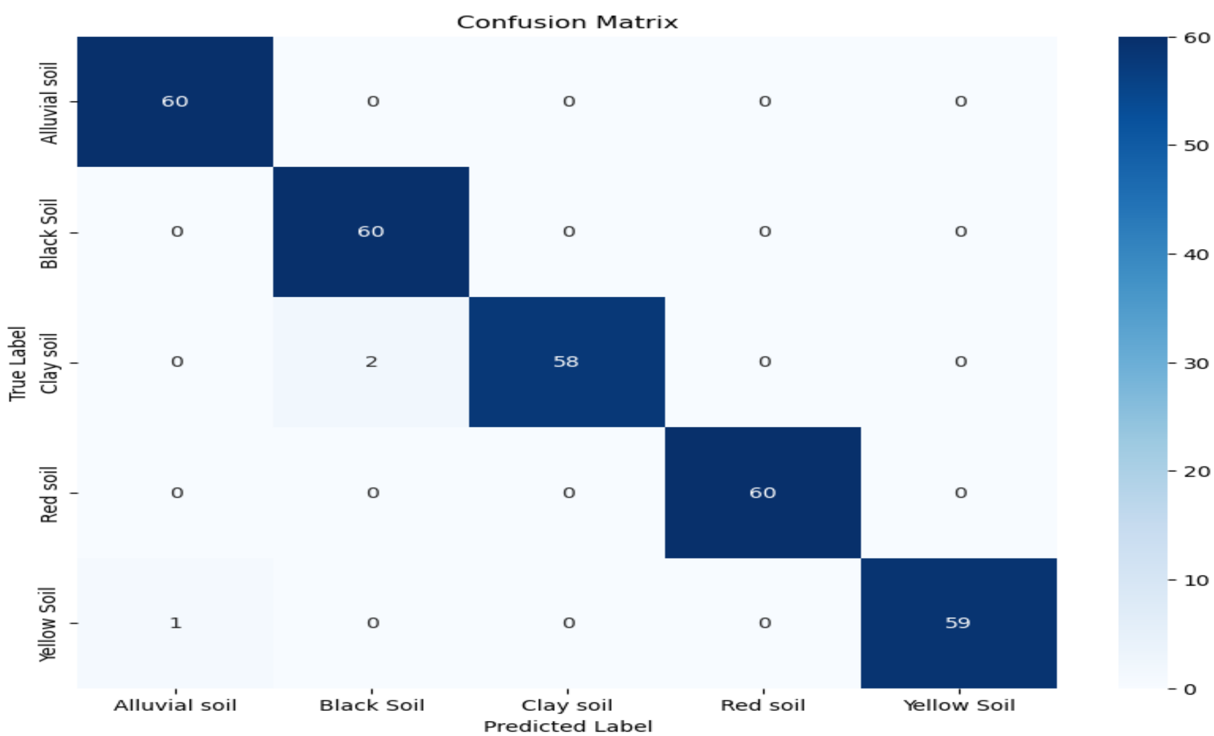

Figure 3: Confusion Matrix Analysis

Training and Validation Accuracy/Loss Graph : The training and validation accuracy curves in figure 4 exhibited a steady rise, while the loss curves showed a consistent decrease, confirming the model's generalization capability across unseen data.

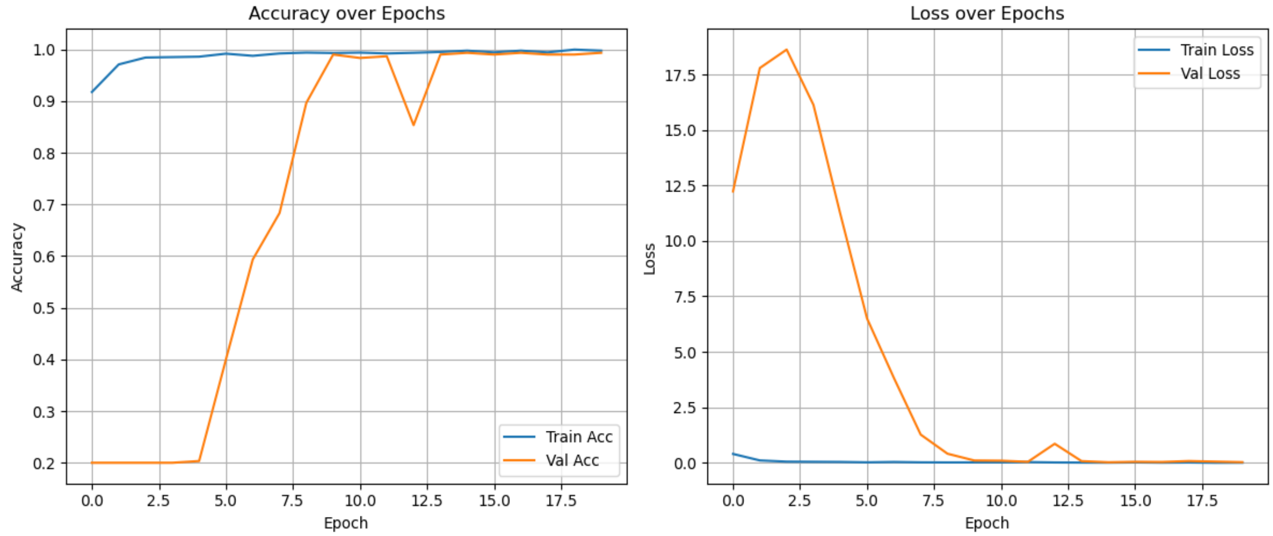

Figure 4: Training and Validation Accuracy/Loss Graph

Prediction Results Analysis (Best and Worst Cases): From figure 5 it is clearly seen that in the best predictions, **Red Soil** was classified accurately with high precision, showing distinct and consistent features. In the worst predictions, **Clay Soil** exhibited behavior similar to **Black Soil**, and **Yellow Soil** was misclassified as **Alluvial Soil**, likely due to their visual similarities.

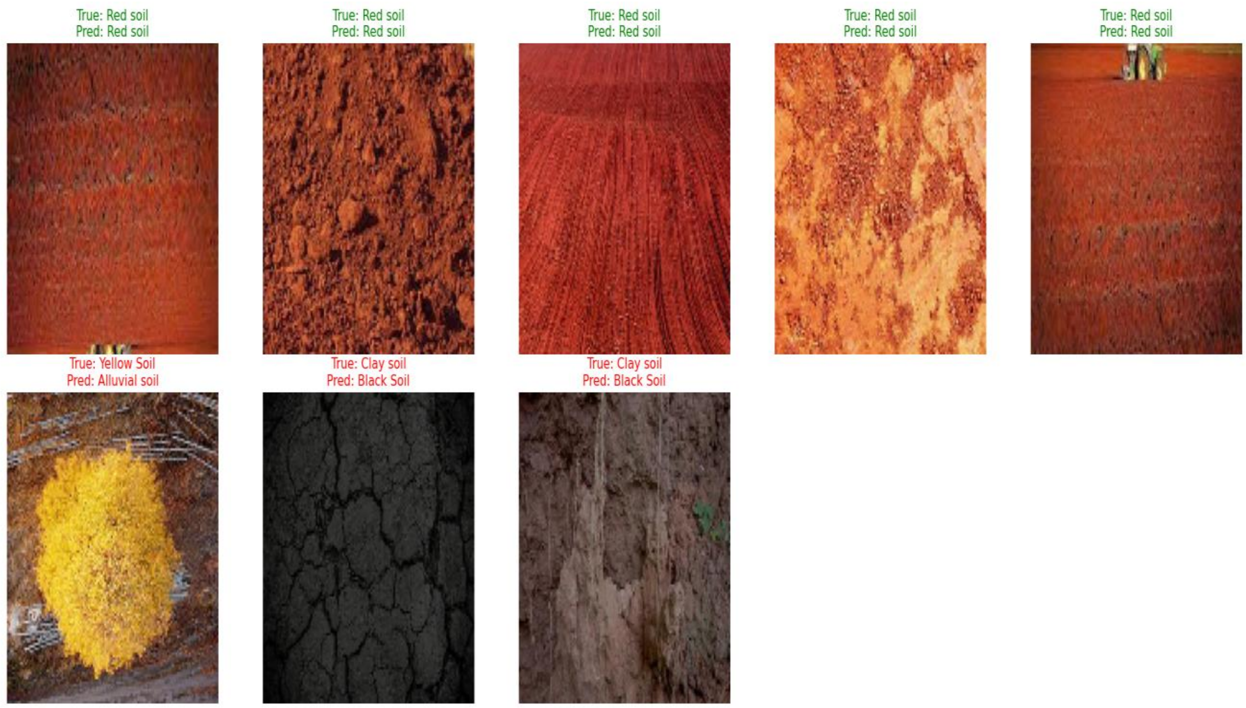

Figure 5: Best vs Worst Prediction

While the current CNN model demonstrates high accuracy on the preprocessed dataset, future improvements could involve incorporating more diverse samples, advanced augmentation techniques, and exploring deeper or hybrid network architectures for even higher generalization performance. Additionally, in the future, we can leverage more advanced deep learning models and work with a larger number of soil classes to further enhance the model's capabilities. Moreover, this soil classification model could be integrated into a crop recommendation system, offering valuable insights for agricultural applications.

5. CONCLUSION

This study emphasizes the evolving landscape of soil classification techniques, highlighting the effectiveness of both traditional ma chine learning models and modern deep learning approaches. Through an extensive review, it was observed that while Random Forest and SVM excel in classifying soils based on physicochemical data, CNNs and their hybrid variants offer superior capabilities in handling image-based soil classification tasks.

Experimentally, a custom-built CNN model demonstrated remarkable performance, achieving 98% classification accuracy across five balanced soil classes. Careful preprocessing, balanced augmentation, optimized architecture design, and appropriate training strategies significantly contributed to this success. Evaluation using precision, recall, F1-score, and confusion matrices further validated the robustness of the proposed model.

Future directions include expanding the dataset to encompass more soil types and a larger volume of images, thereby enhancing model generalization. Moreover, integrating soil classification outputs with crop recommendation and prediction frameworks could substantially benefit precision agriculture practices, contributing towards sustainable agricultural development.

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